

September 4, 2025

6.S894

Accelerated Computing

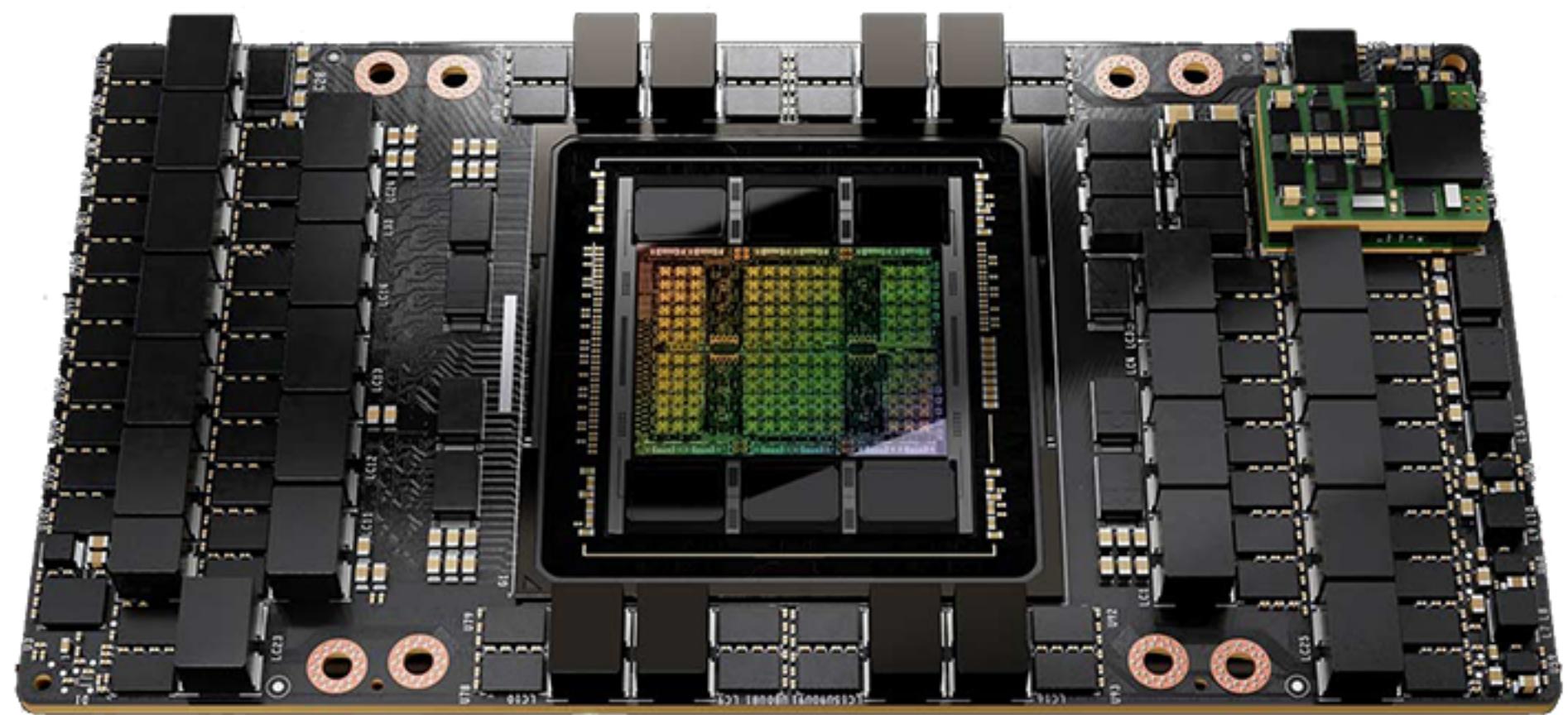
Lecture 1: The Problem

Jonathan Ragan-Kelley 

Hardware is amazing today



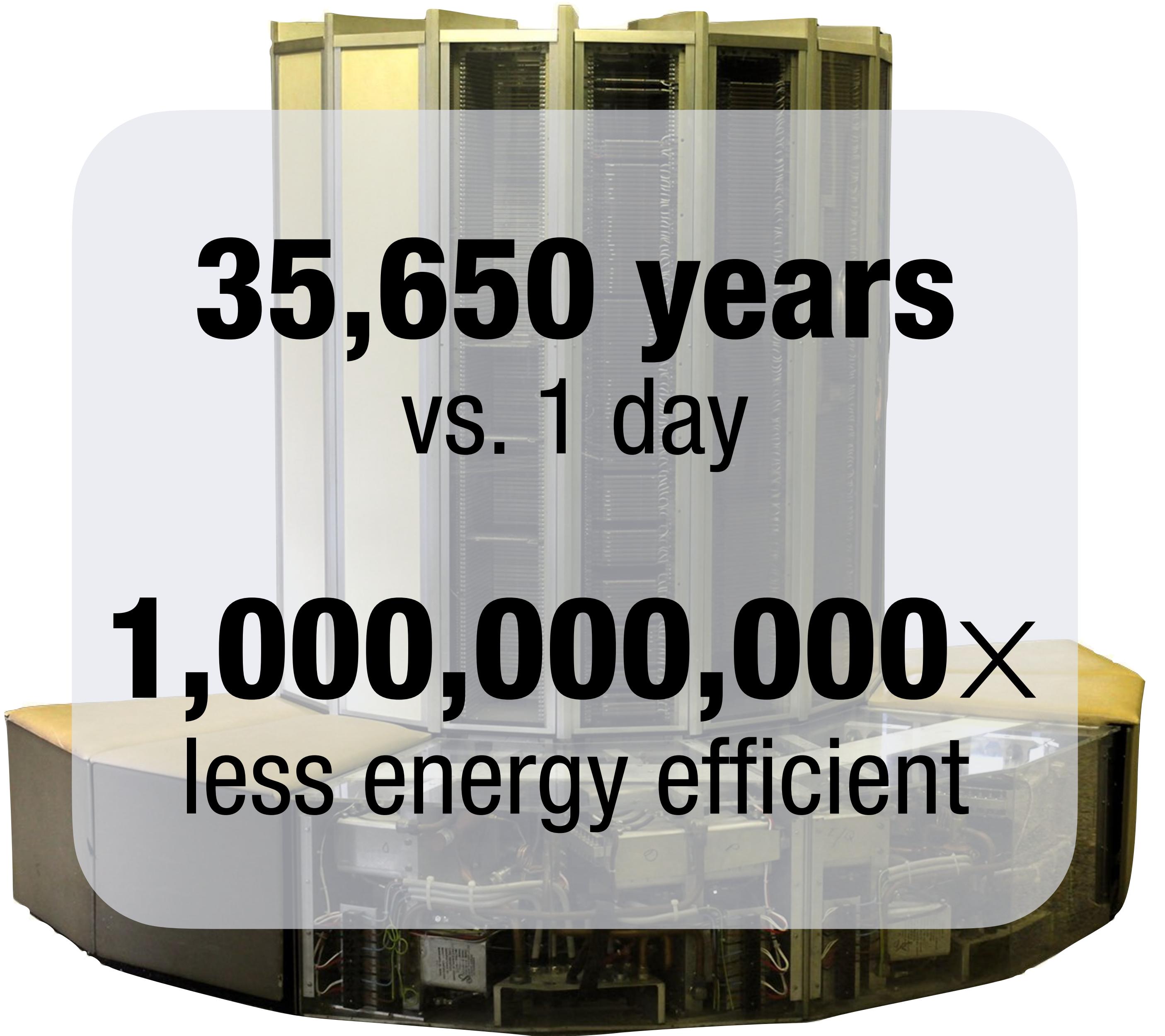
LLaMA
by  Meta



1B parameters
 \times 30B tokens
 \times 6 FLOPS/parameter

1 day
on 8 GPUs

180 ExaFLOPS (16-bit)



35,650 years
vs. 1 day

1,000,000,000×
less energy efficient

Cray 1 (1975)

the first “supercomputer”

160 MegaFLOPS
8MB RAM

115 kW

\$7.9M
(\$56M in 2025 dollars)

50 years isn't as long as it sounds

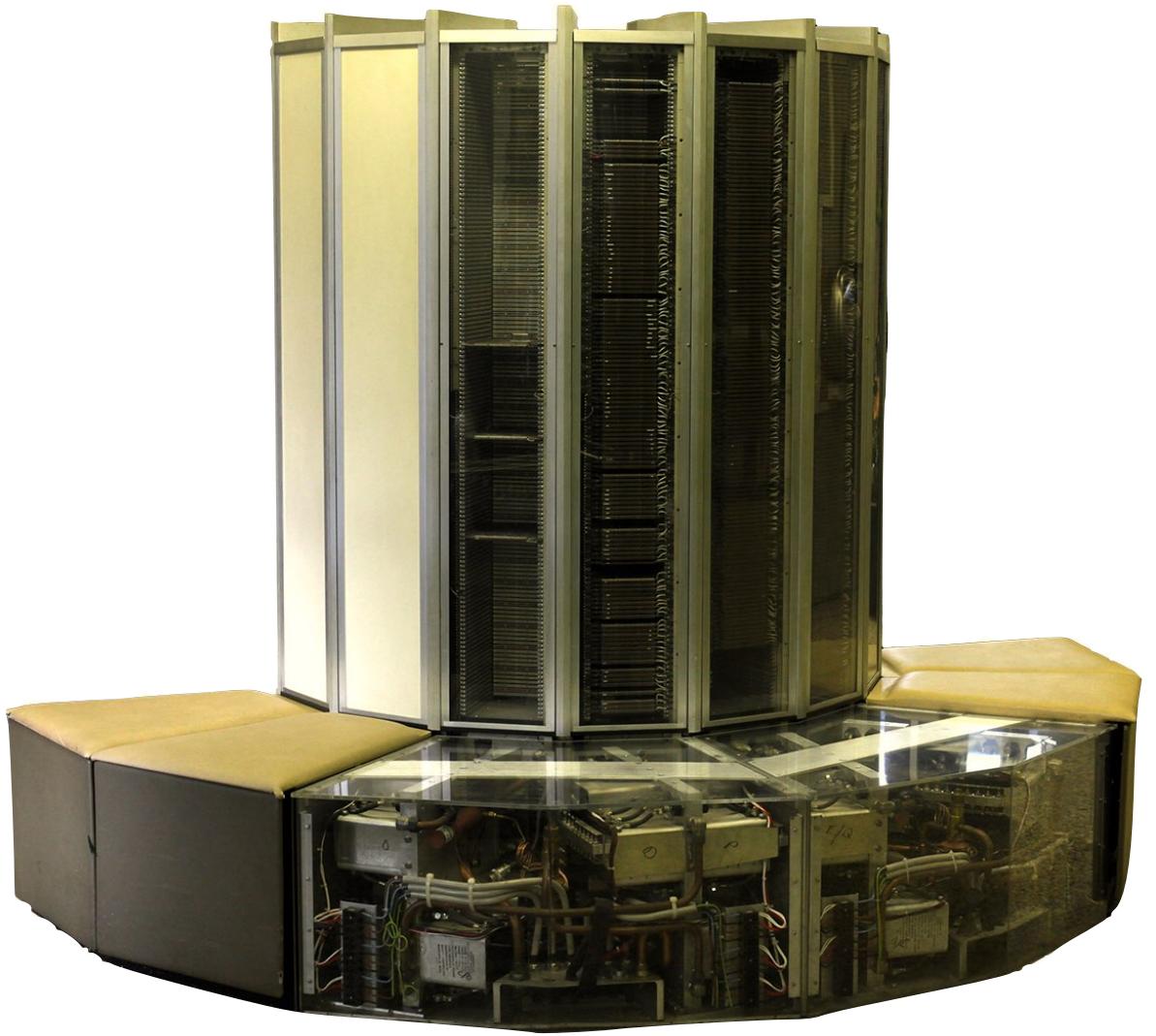


115 mph • 22 mpg



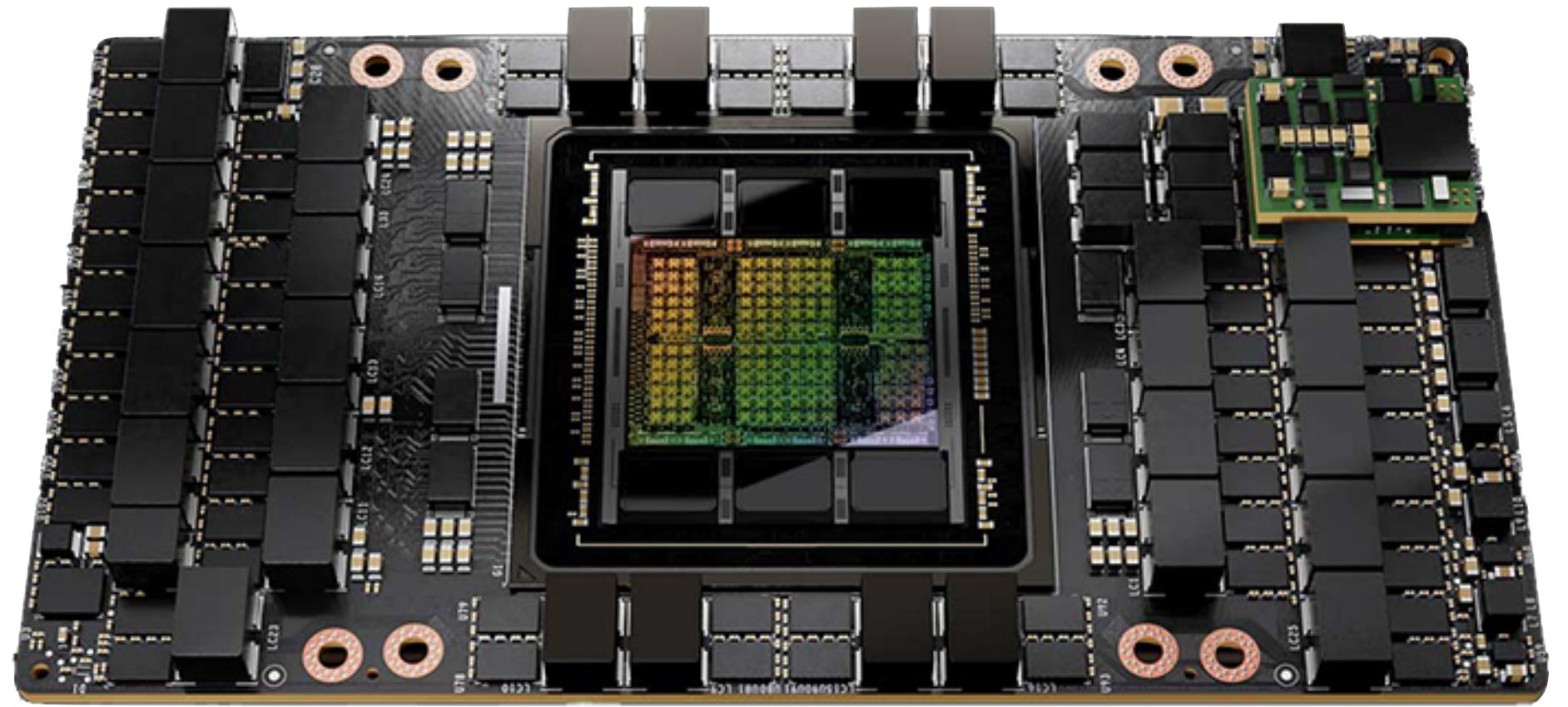
560 mph

1975



700 Watts / MegaFLOP

2024



700 Watts / PetaFLOP
1,000,000,000×



~20 TeraFLOPs

Let's multiply some matrices

Python

```
# A,B,C : List[float]
# N = 2048
for i in range(N):
    for j in range(N):
        for k in range(N):
            C[i*N + j] += A[i*N + k] * B[k*N + j]
```

Apple M2



~20 TeraFLOPs

10 MegaFLOPS

0.00005% of SoC peak

Let's multiply some matrices

JavaScript

```
// A,B,C : Array<number>
// N = 2048
for (let i = 0; i < N; i++) {
  for (let j = 0; j < N; j++) {
    for (let k = 0; k < N; k++) {
      C[i*N + j] += A[i*N + k] * B[k*N + j];
    }
}
```

500 MegaFLOPS

0.0025% of SoC peak

Apple M2



~20 TeraFLOPs

Let's multiply some matrices

C (clang18 -O3 -march=native ...)

```
// float *A, *B, *C
// N = 2048
for (int i = 0; i < N; ++i) {
    for (int j = 0; j < N; ++j) {
        for (int k = 0; k < N; ++k) {
            C[i*N + j] += A[i*N + k] * B[k*N + j];
    }
}
```

Apple M2



~20 TeraFLOPs

1 GigaFLOPS

0.005% of SoC peak

Let's multiply some matrices

C (clang18 -O3 -march=native ...)

```
// float *A, *B, *C
// N = 2048
for (int i = 0; i < N; ++i) {
    for (int k = 0; k < N; ++k) {
        for (int j = 0; j < N; ++j)
            C[i*N + j] += A[i*N + k] * B[k*N + j];
    }
}
```

Apple M2



~20 TeraFLOPs

20 GigaFLOPS

0.1% of SoC peak

Let's multiply some matrices

C (clang18 -O3 -march=native ...)

// float* A = ...
// N = 2048
for (int i = 0; i < N; ++i) {
 for (int k = 0; k < N; ++k) {
 for (int j = 0; j < N; ++j) {
 C[i][j] += A[i][k] * B[k][j];
 }
 }
}

40 GigaFLOPS

0.2% of SoC peak

Apple M2



~20 TeraFLOPs

Let's multiply some matrices

C (clang18 -O3 -march=native ...)

// float* A = ...
// N = 2048
for (int i = 0; i < N; ++i) {
 for (int k = 0; k < N; ++k) {
 for (int j = 0; j < N; ++j) {
 C[i][j] += A[i][k] * B[k][j];
 }
 }
}

+ hand-tuned,
vectorized,
cache blocked
+ parallel
(4+4 cores)

200 GigaFLOPS

1% of SoC peak

Apple M2



~20 TeraFLOPs

Let's multiply some matrices

C & Assembly (Apple Accelerate)

```
// float *A, *B, *C  
// N = 2048  
for (int i = 0; i < N; i++) {  
    for (int k = 0; k < N; k++) {  
        for (int j = 0; j < N; j++) {  
            C[i][j] += A[i][k] * B[k][j];  
        }  
    }  
}
```

+ hand-tuned,
cache blocked
+ quantized to bf16,
+ matrix units

1.5 TeraFLOPS

7.5% of SoC peak

Apple M2



~20 TeraFLOPs

Let's multiply some matrices

Metal compute shaders

```
static inline void accumulateOuterProduct(
    const device float4& inputA,
    const device float4& inputB,
    thread float4x4& output
)
{
    output[0] += inputA.x * inputB;
    output[1] += inputA.y * inputB;
    output[2] += inputA.z * inputB;
    output[3] += inputA.w * inputB;
}

// Each thread of this kernel operates on a 8x8 sector of the
// output buffer. Matrix buffers require padding to accomodate this.
// Requirements:
// The bytes-per-row of each matrix buffer must be padded to a multiple
// of eight floats (32 bytes). Similarly, the row count of each matrix
// must be padded to a multiple of eight.
kernel void MultiplyMatrices(
    constant BufferDimensions& dimensions [[ buffer(0) ]],
    const device float4* inputA [[ buffer(1) ]],
    const device float4* inputB [[ buffer(2) ]],
    device float4* output [[ buffer(3) ]],
    ushort2 outputSector [[ thread_position_in_grid ]]
)
{
    const ushort2 outputPosition = outputSector * sectorSize;
    if (
        outputPosition.x >= dimensions.outputRowCount ||
        outputPosition.y >= dimensions.outputColumnCount
    )
    {
        return;
    }

    float4x4 s00 = float4x4(0.f), s01 = float4x4(0.f);
    float4x4 s10 = float4x4(0.f), s11 = float4x4(0.f);
    inputA += outputPosition.x / 4;
    inputB += outputPosition.y / 4;

    const Dimension strideA = dimensions.bytesPerRowA / sizeof(float4);
    const Dimension strideB = dimensions.bytesPerRowB / sizeof(float4);
    const device float4* const endOffB = inputB + dimensions.innerInputDimension * strideB;

    while (inputB < endOffB) {
        accumulateOuterProduct(inputA[0], inputB[0], s00);
        accumulateOuterProduct(inputA[0], inputB[1], s01);
        accumulateOuterProduct(inputA[1], inputB[0], s10);
        accumulateOuterProduct(inputA[1], inputB[1], s11);

        inputA += strideA;
        inputB += strideB;

        const Dimension outputStride = dimensions.outputBytesPerRow / sizeof(float4);
        output += outputPosition.x * outputStride + outputPosition.y / 4;

        output[0] = s00[0]; output[1] = s01[0]; output += outputStride;
        output[0] = s00[1]; output[1] = s01[1]; output += outputStride;
        output[0] = s00[2]; output[1] = s01[2]; output += outputStride;
        output[0] = s00[3]; output[1] = s01[3]; output += outputStride;
        output[0] = s10[0]; output[1] = s11[0]; output += outputStride;
        output[0] = s10[1]; output[1] = s11[1]; output += outputStride;
        output[0] = s10[2]; output[1] = s11[2]; output += outputStride;
        output[0] = s10[3]; output[1] = s11[3];
    }
}
```

1000s of
lines...

Apple M2



~20 TeraFLOPs

3.2 TeraFLOPS
15% of SoC peak

Let's multiply some matrices

Neural Engine

Proprietary ISA
& interface

int16 quantized

16 TeraOPS

80% of SoC peak

Apple M2



~20 Tera(FL)OPs

Version % Peak

NPU 80%

GPU 15%

CPU Matrix 7.5%

Opt. Par. C 1%

Opt. C 0.2%

C 0.005%

JavaScript 0.0025%

Python 0.00005%

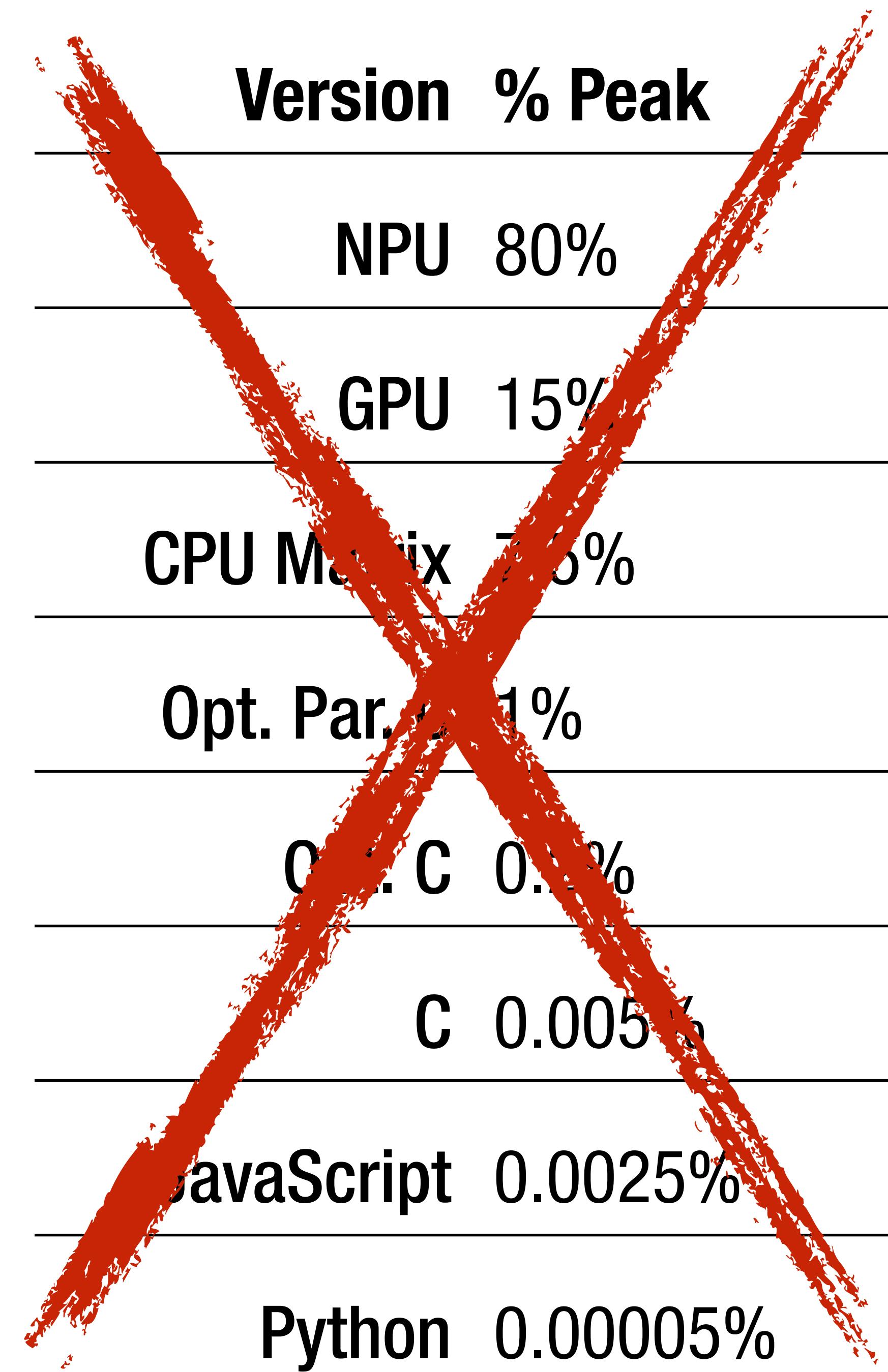
6 orders of magnitude performance & efficiency

Extreme programming effort & specialization of code

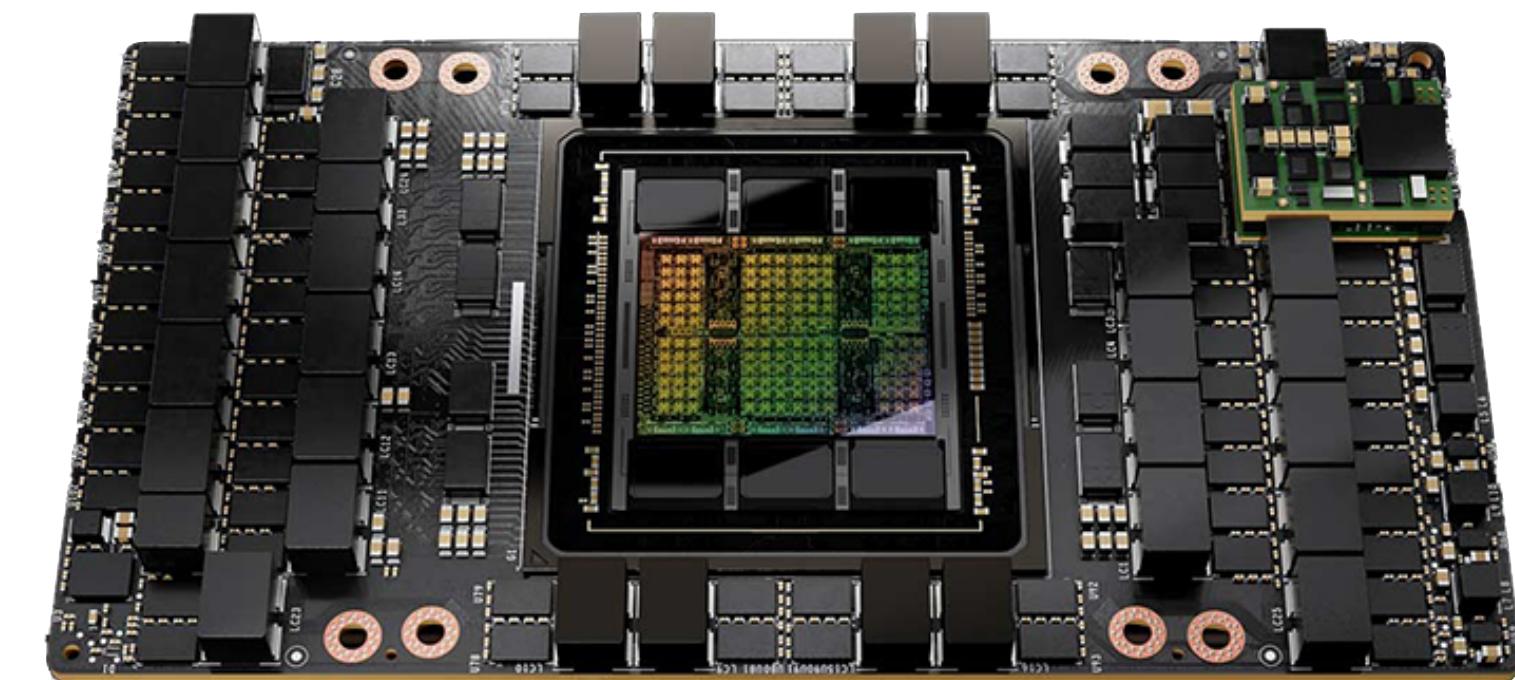
Apple M2



~20 Tera(FL)OPs



NVIDIA H100



~1000 TeraFLOPs

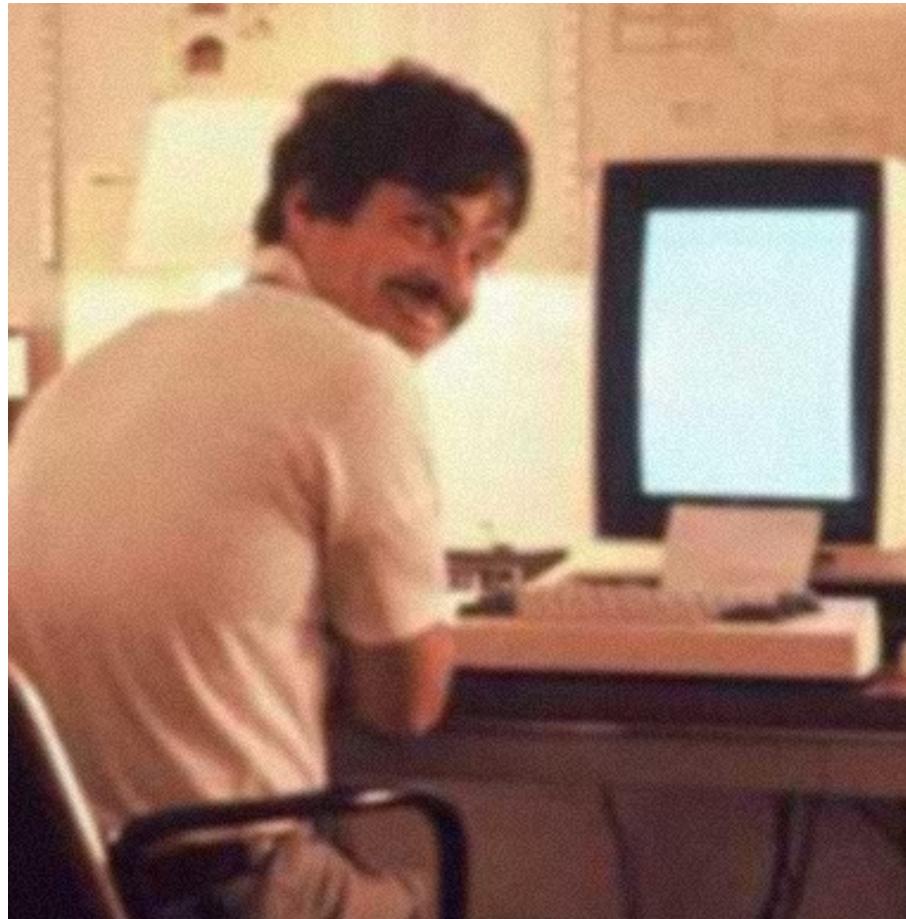
Hardware is amazing, but...

the gap between
reasonable code
and peak performance
is enormous.

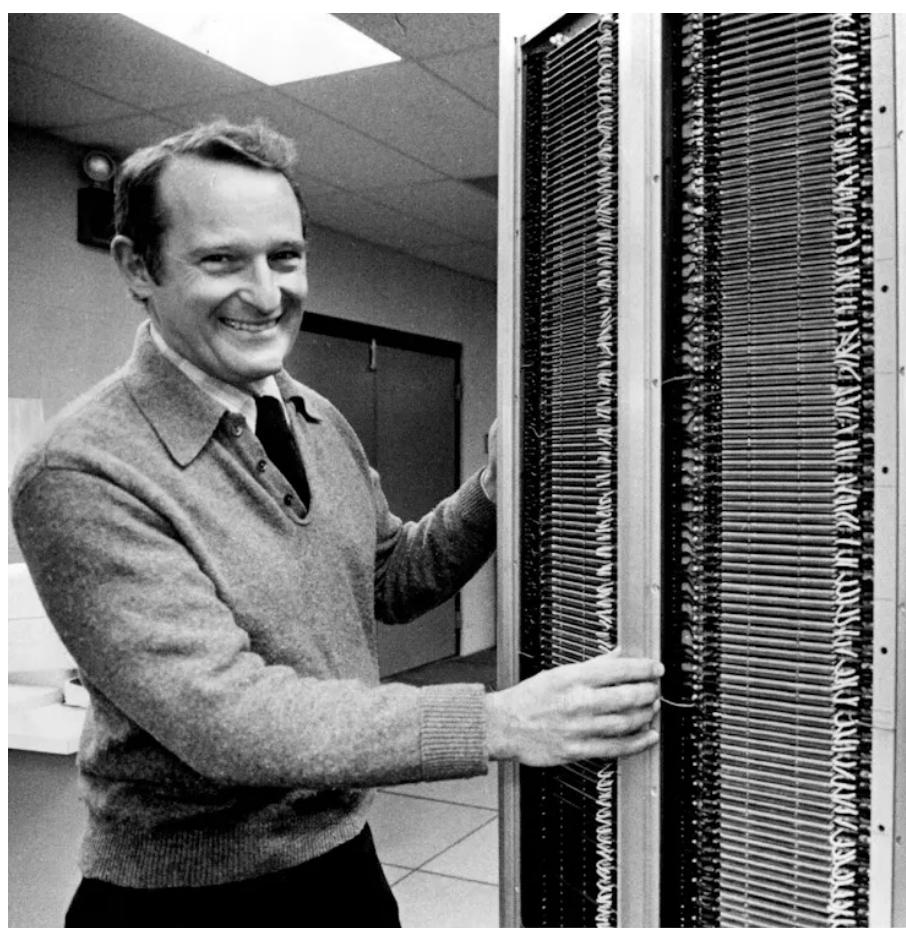
clean,
modular,
portable...

Why does this gap exist?

**Hardware has
radically changed**



**Software
largely hasn't**



1975 had:

- UNIX
- C
- virtual memory
- optimizing compilers
- ML, type inference
- Smalltalk
- Networked GUI workstations

Increasing gap between Programming Models and Hardware

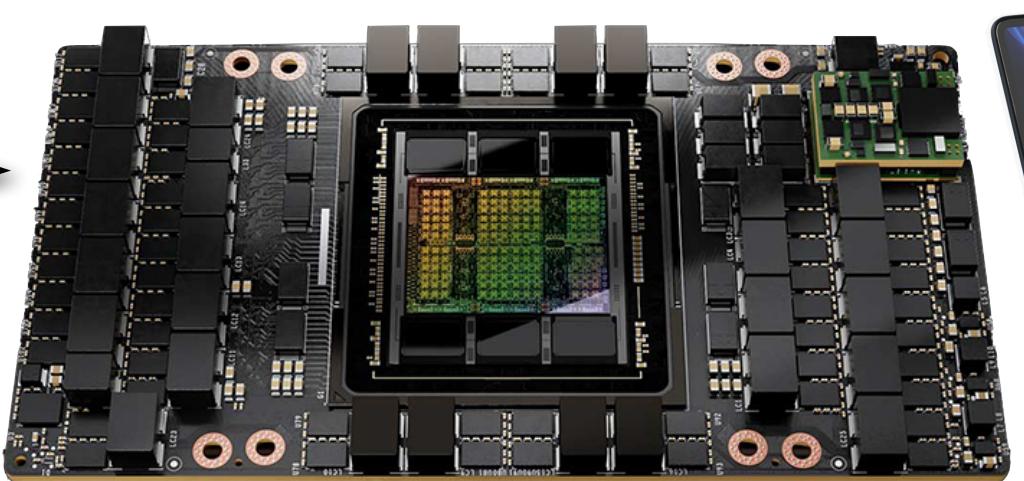
Sequential, scalar
primitive computation

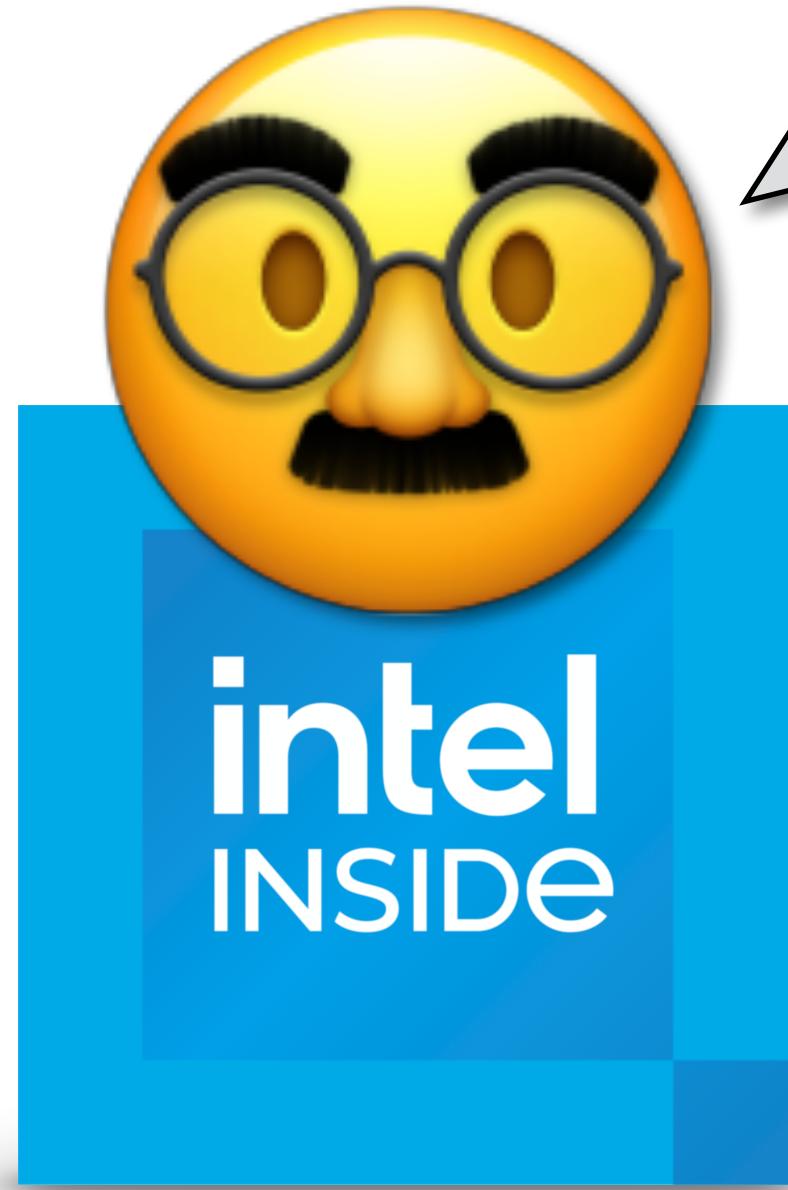
Uniform global
heap memory

**Abstraction through
subroutines & pointers**

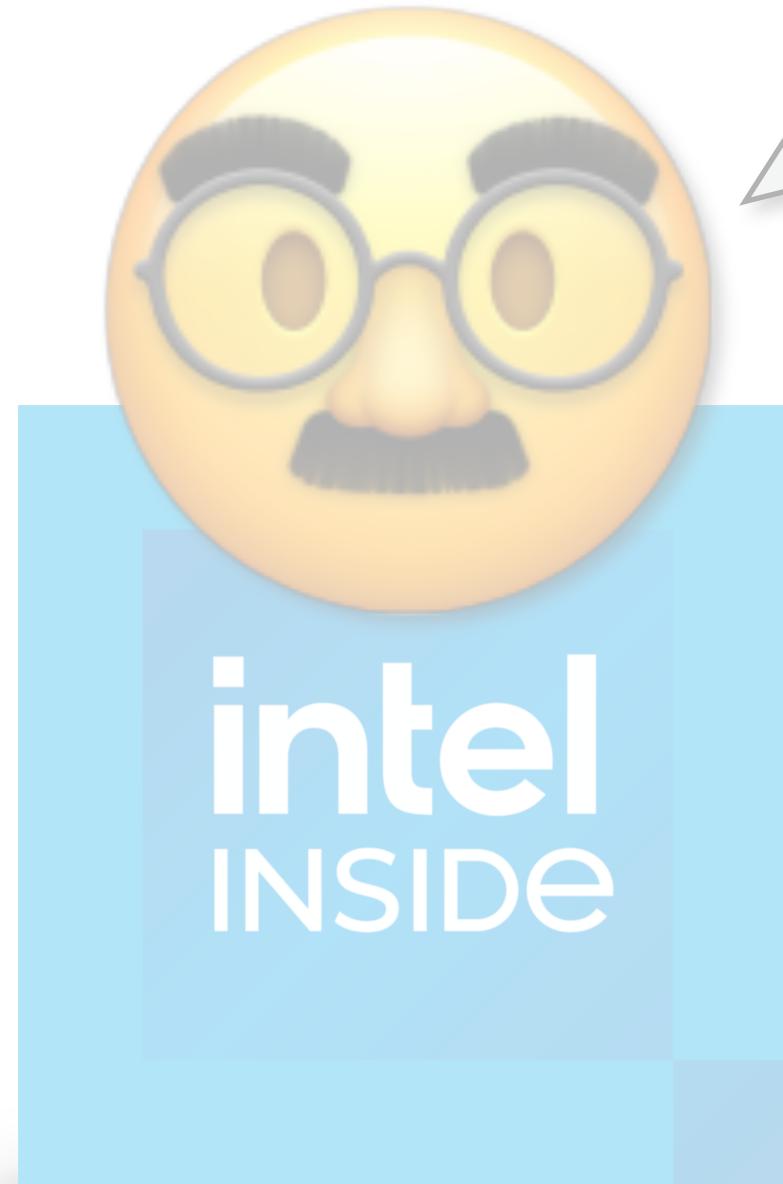
Looks
about right

LOLWUT!?





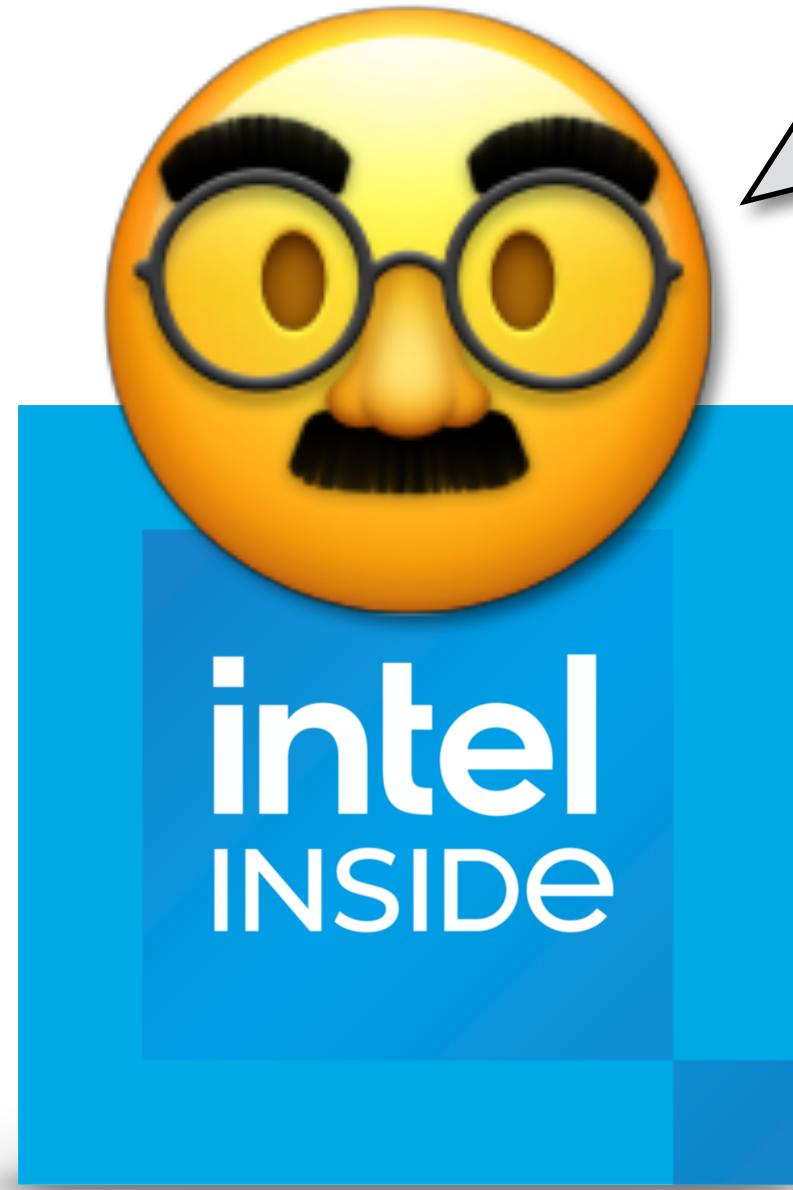
Why yes,
I am still
basically a
PDP-11



Why yes,
I am still
basically a
PDP-11

You will **rewrite**
all your code in
CUDA . . .
and pray I don't
alter the deal
any further!





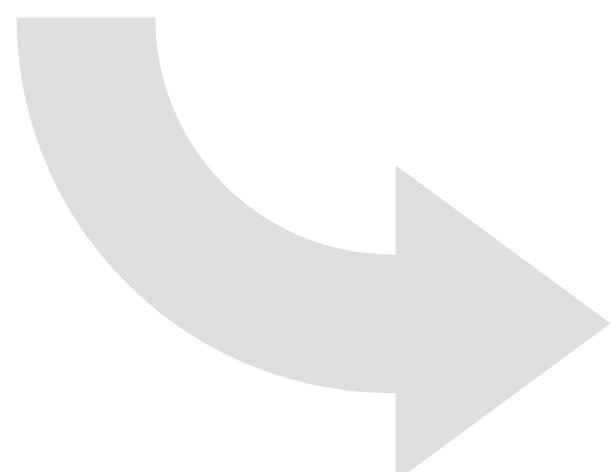
Why yes,
I am still
basically a
PDP-11

Was there ever
anything else?



...

To unlock the potential
of hardware,
we need to rethink how
we program.



1

Better understand
hardware

What makes hardware fast?

Executing a sequential stream of instructions in as little time as possible



A simple processor

1. Instr. fetch
2. Decode
3. Operand fetch
4. Execute
5. Write back

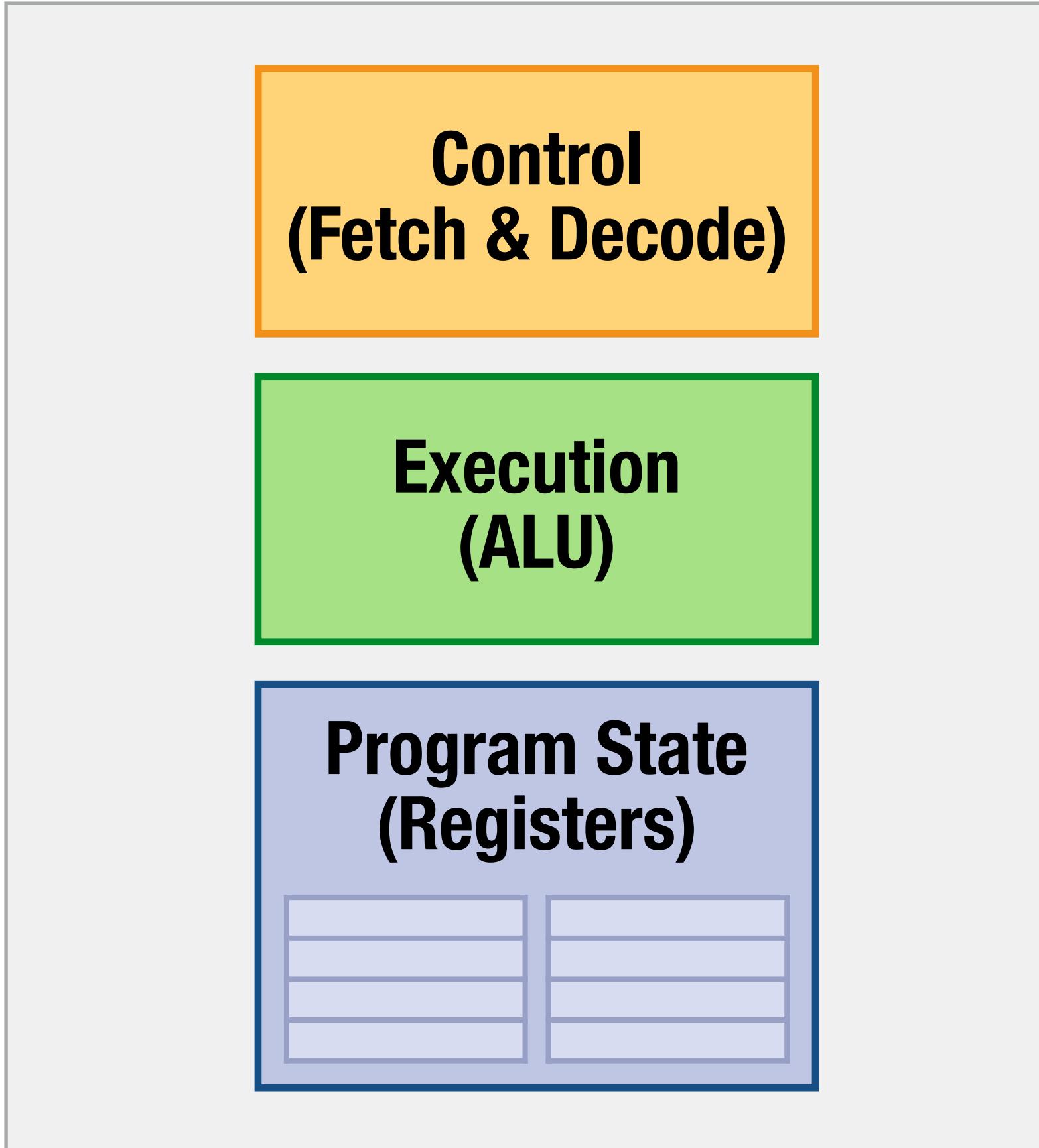
Processor

an interpreter for instructions!

ld	r3, mem[r0+r2]
ld	r4, mem[r1+r2]
mul	r3, r3, r4
add	r5, r5, r3
addi	r2, r2, 4
blt	r2, \$400, LOOP
st	addr[r6], r5
...	

Program

A simple processor



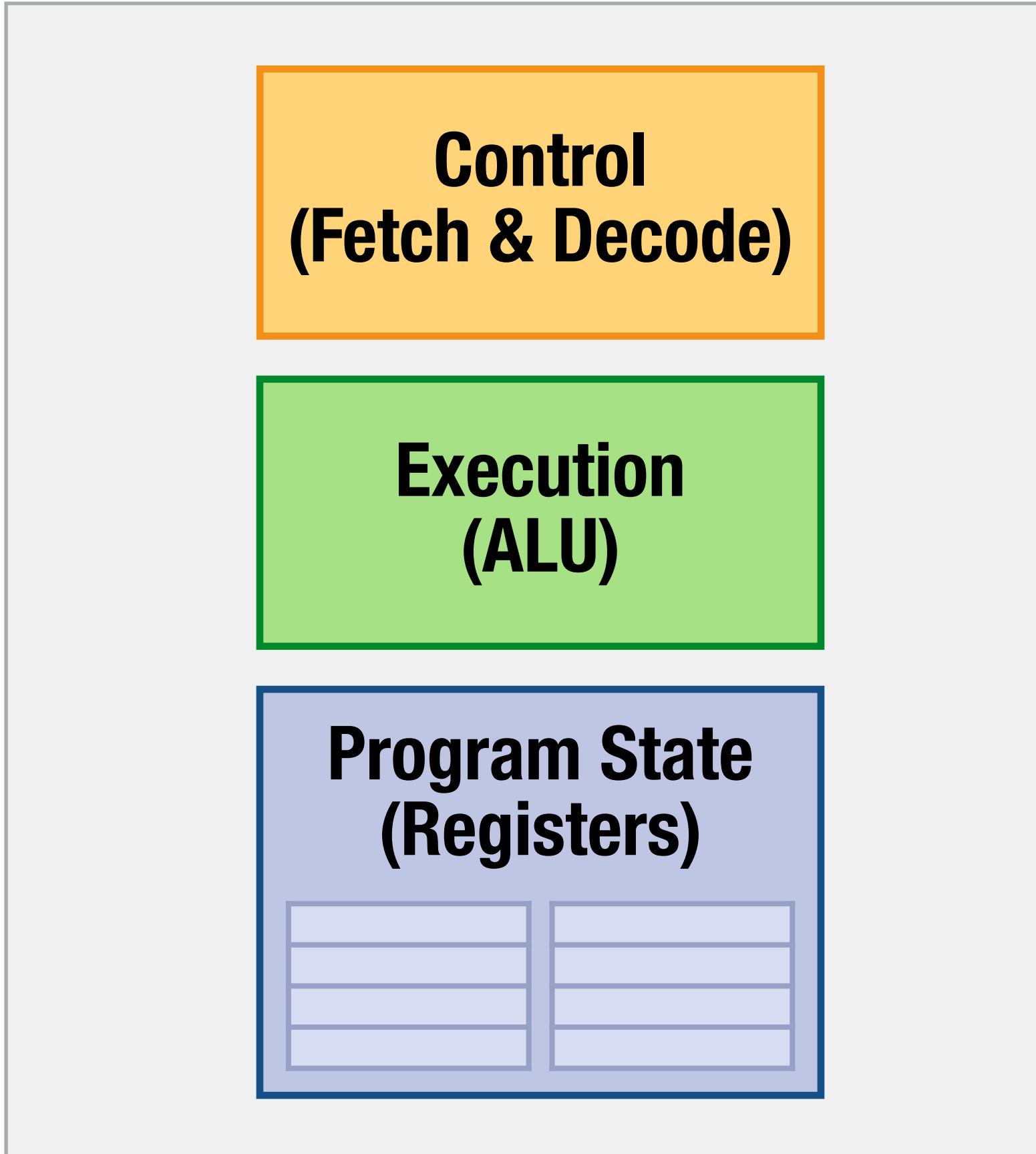
Processor

an interpreter for instructions!

ld	r3, mem[r0+r2]
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add	r5, r5, r3
addi	r2, r2, 4
blt	r2, \$400, LOOP
st	addr[r6], r5
...	

Program

Optimization 1: Increase the clock speed



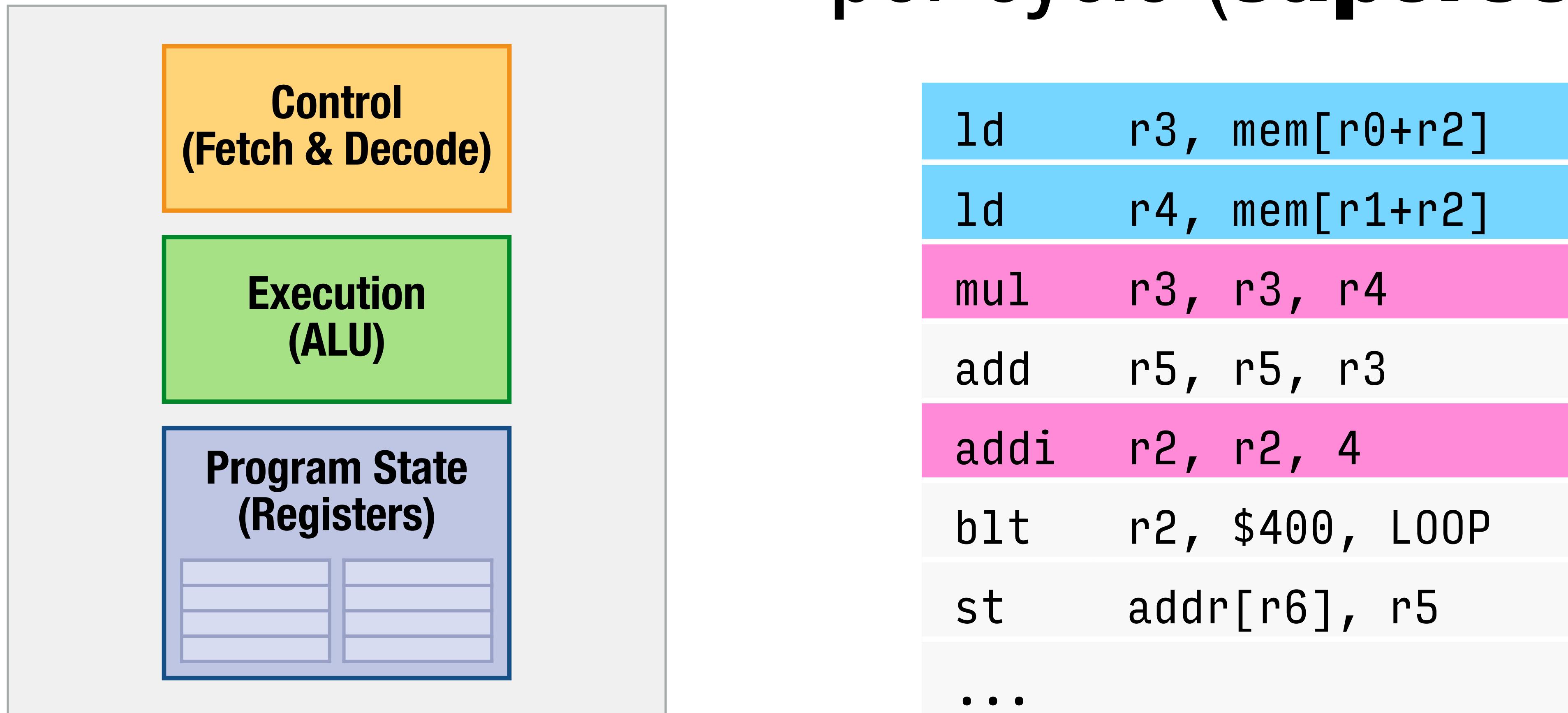
Processor

Higher voltage
↳ power grows with v^2

Faster transistors
↳ higher leakage

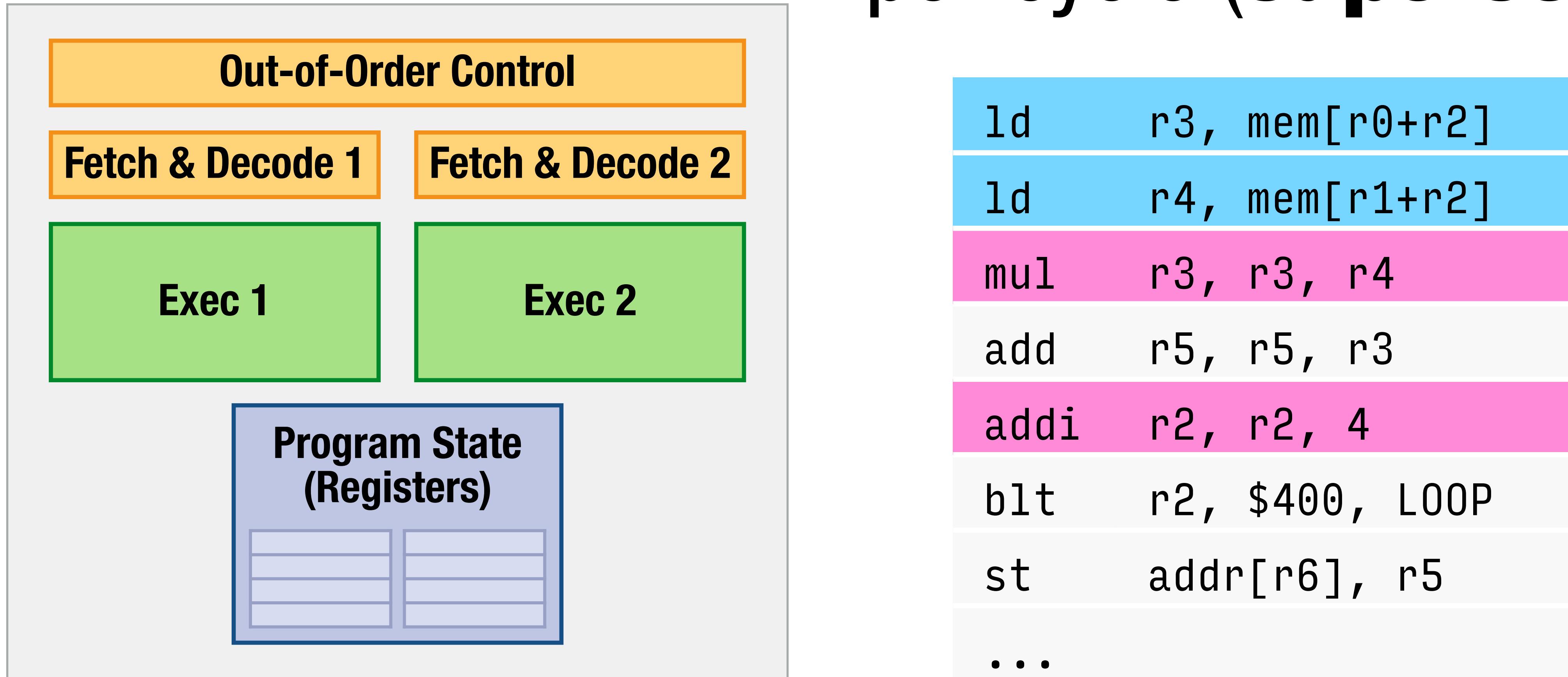
Deeper pipelining
↳ lower average IPC

Optimization 2: Execute multiple instructions per cycle (superscalar)



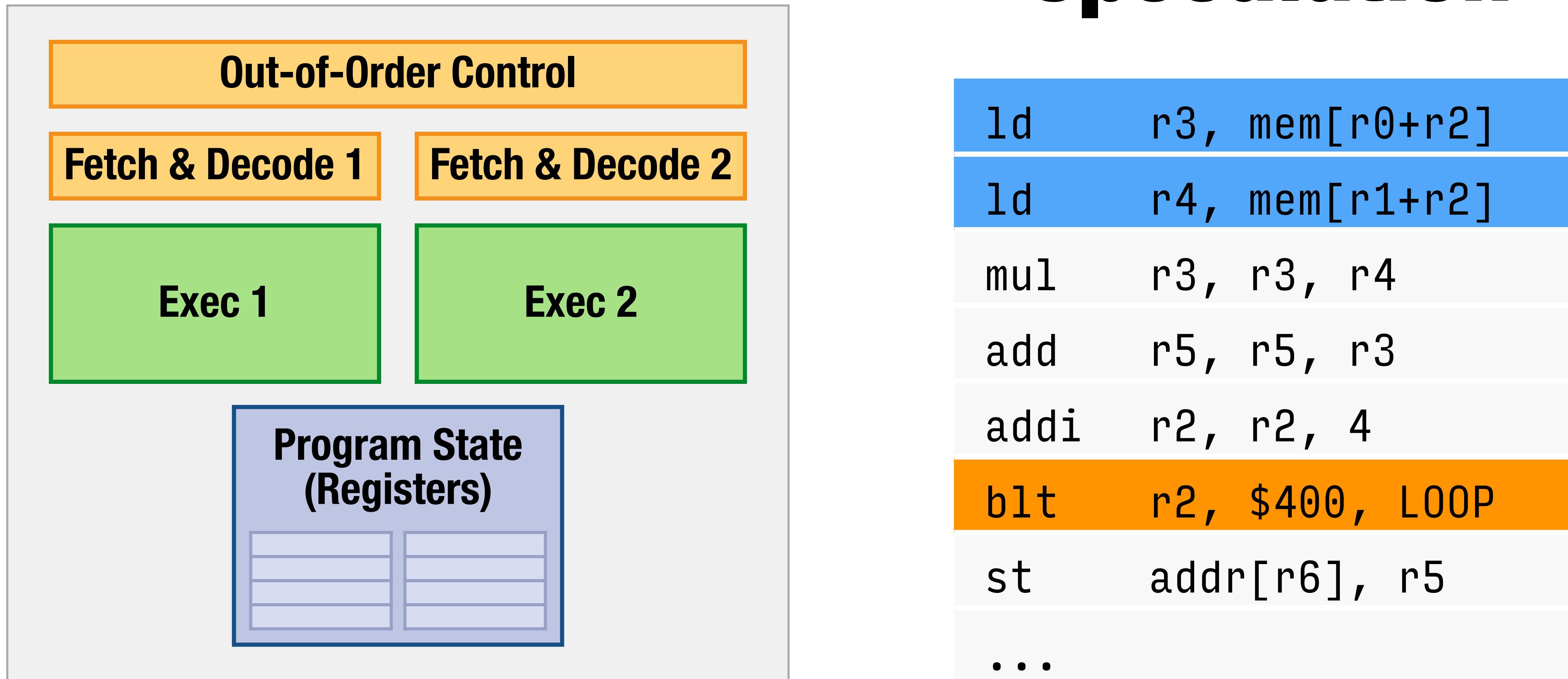
Processor

Optimization 2: Execute multiple instructions per cycle (superscalar)



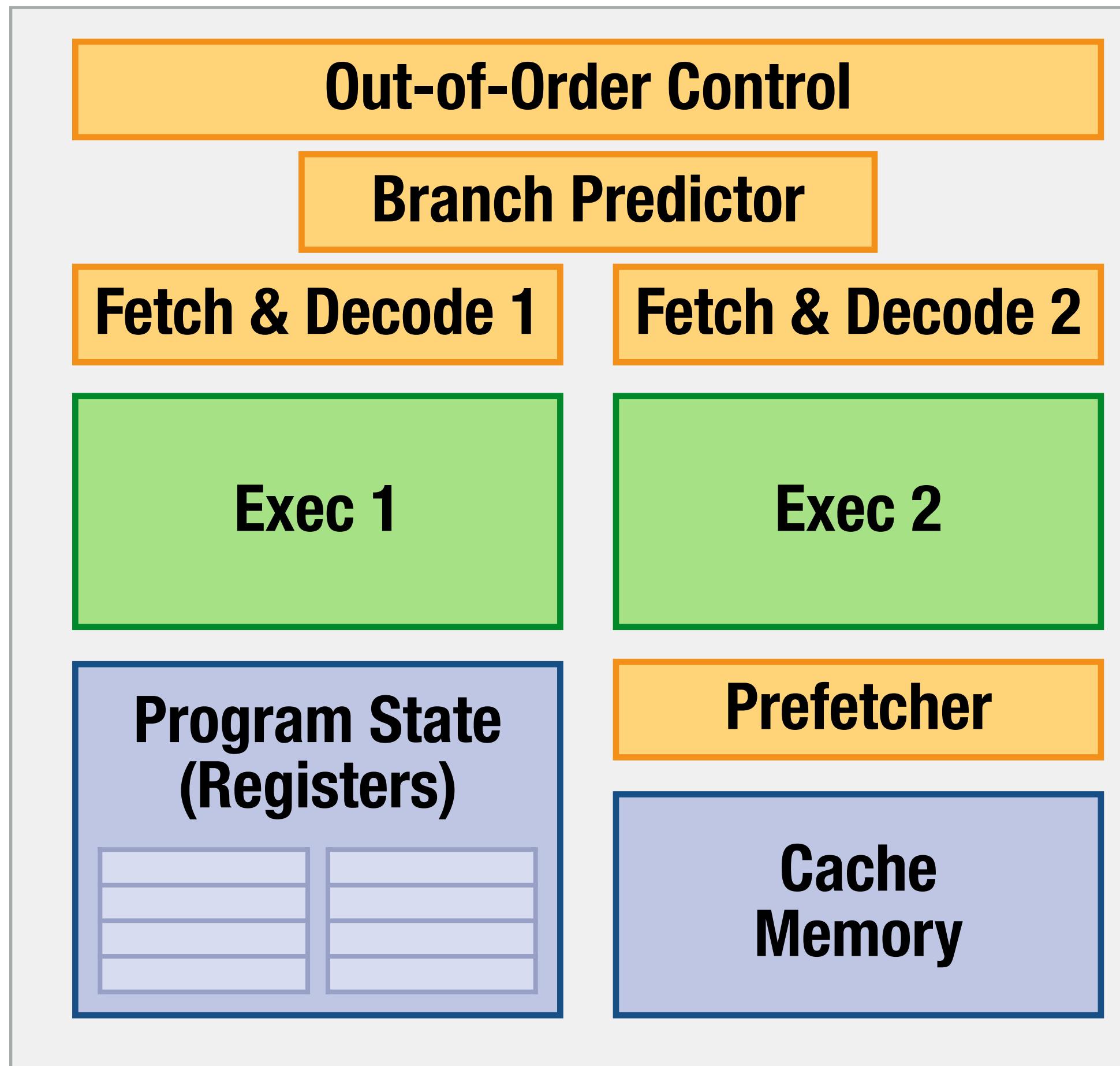
Processor

Optimization 3: Avoid stalls through speculation



Processor

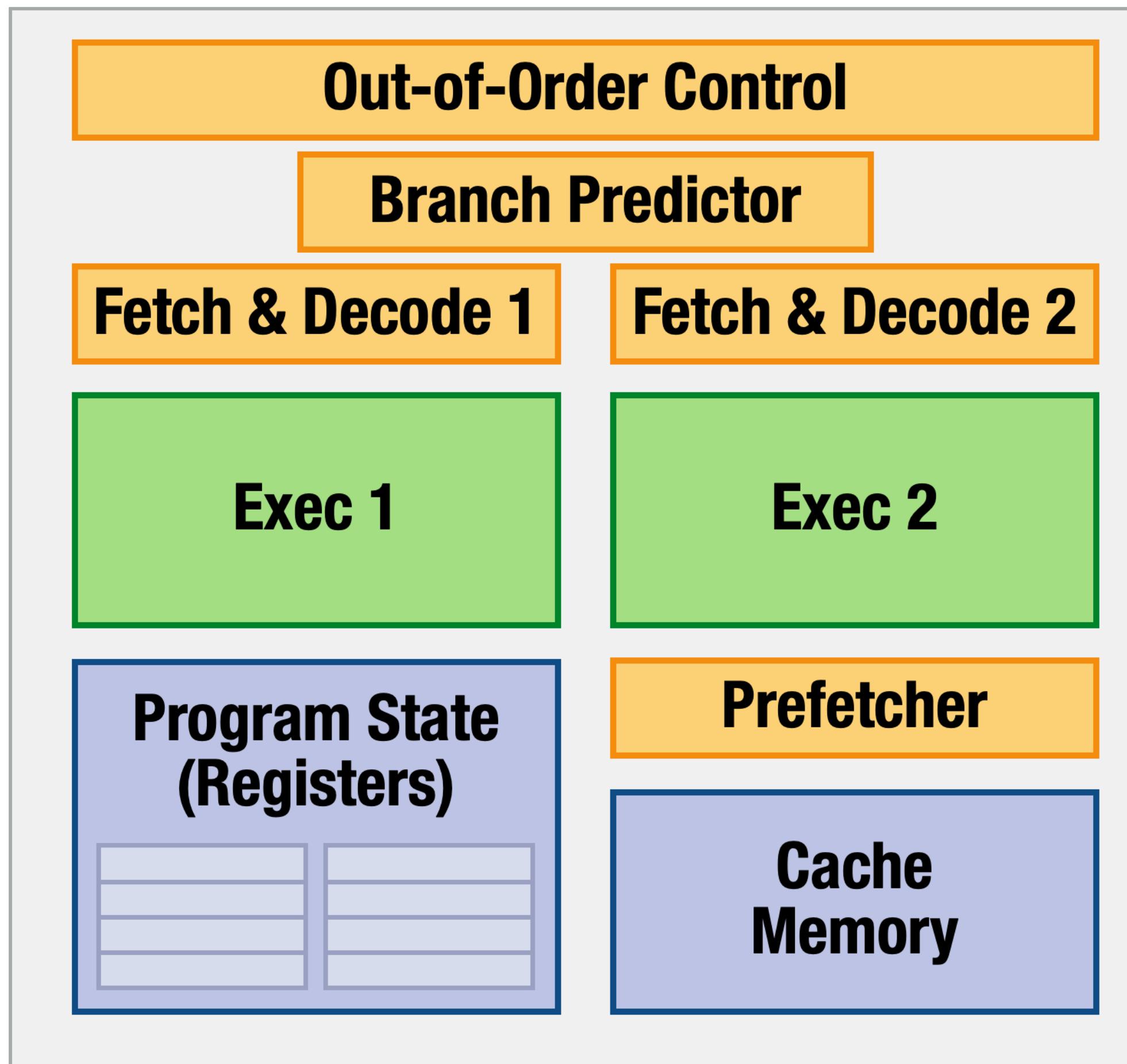
Optimization 3: Avoid stalls through speculation



Processor

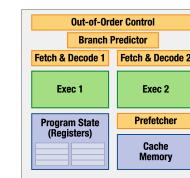
ld	r3, mem[r0+r2]
ld	r4, mem[r1+r2]
mul	r3, r3, r4
add	r5, r5, r3
addi	r2, r2, 4
blt	r2, \$400, LOOP
st	addr[r6], r5
...	

This makes sense when you have only one processor



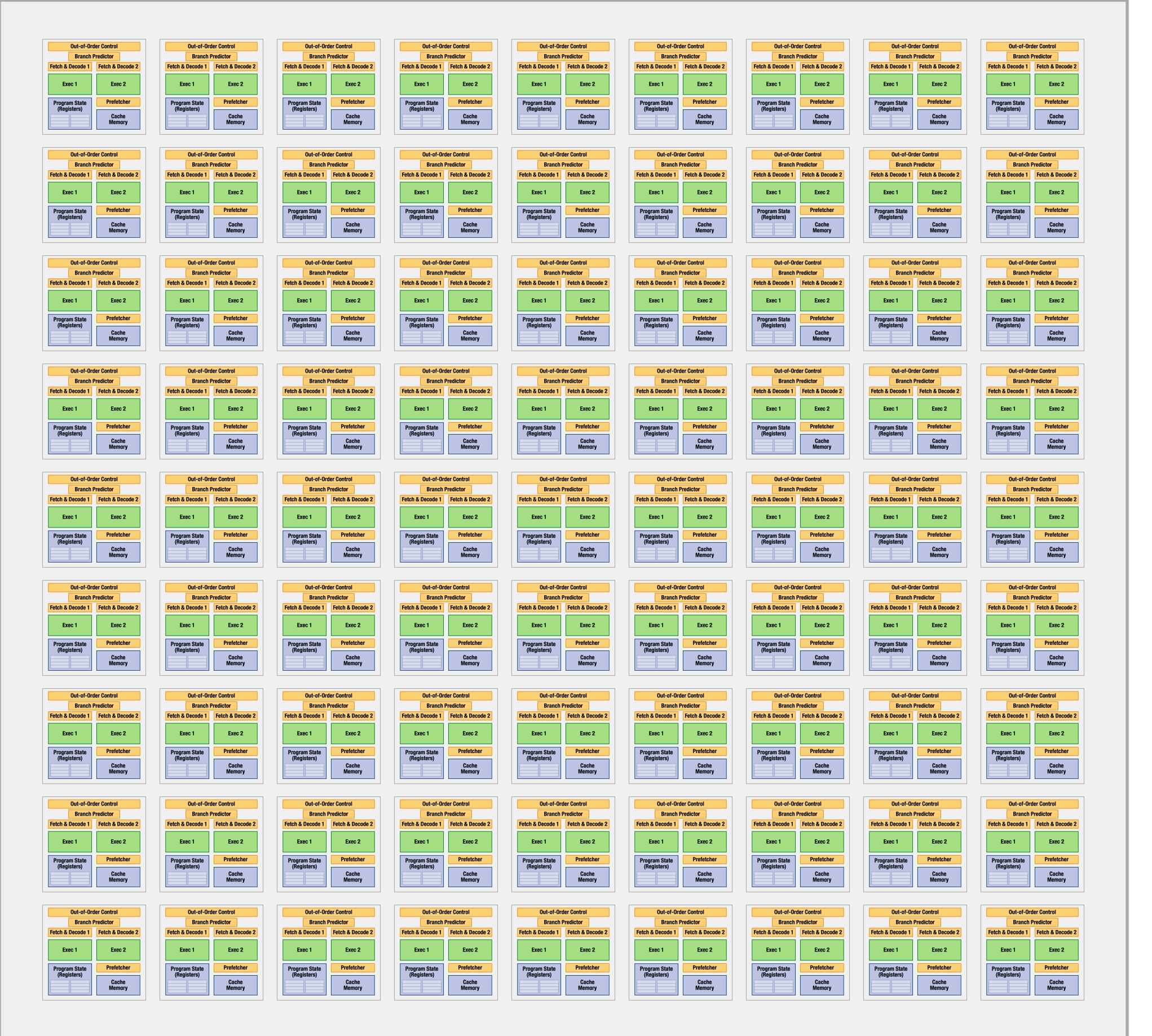
Processor

This makes sense when you have only one processor



Processor (to scale)

The reality today:



At the same time:

We most need
performance when
processing lost of stuff

↳ abundant data-
parallelism

Silicon Chip

A **throughput-oriented**
view of performance:

Optimize aggregate rate
of processing many items

Three things drive throughput:

1

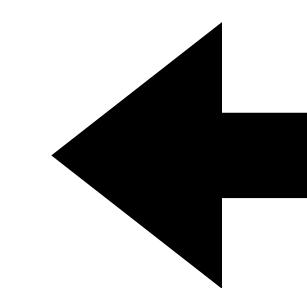
Amount of **work**
to be done

2

Amount of **resources**
to be applied (silicon, energy)

3

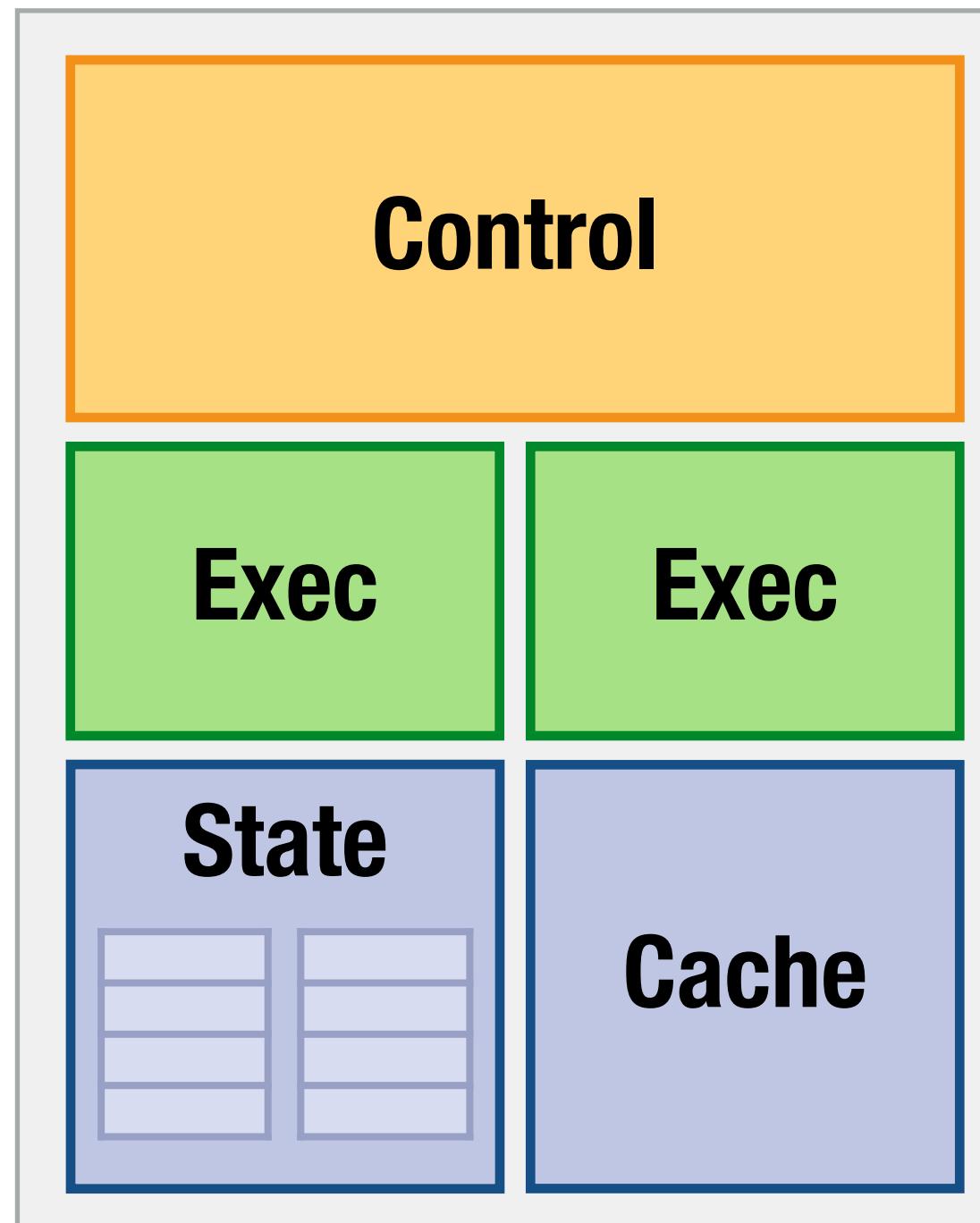
Efficiency of applying
them to useful work



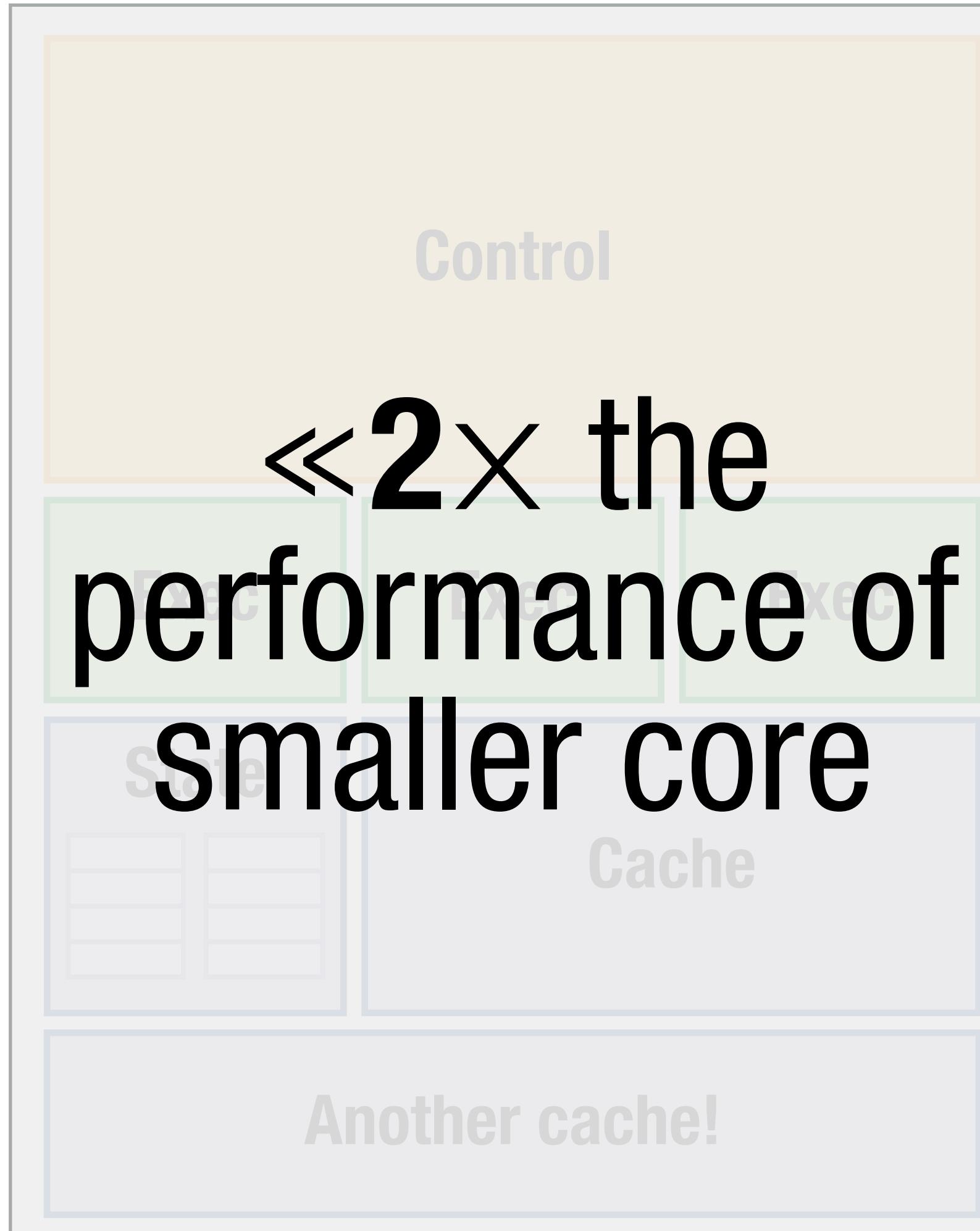
Constraints set
by application

Goal:
optimize this!

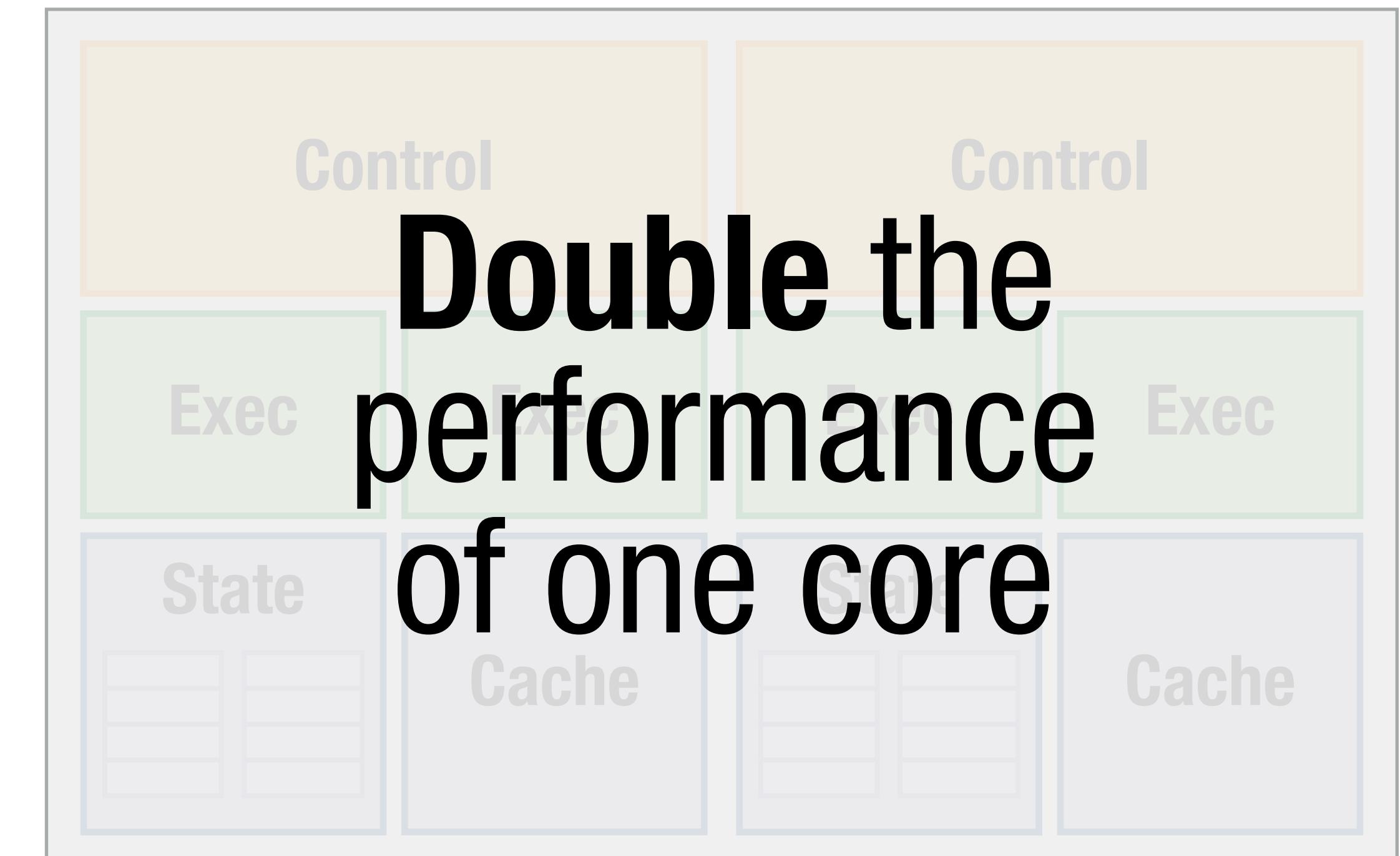
What to do with twice the silicon?



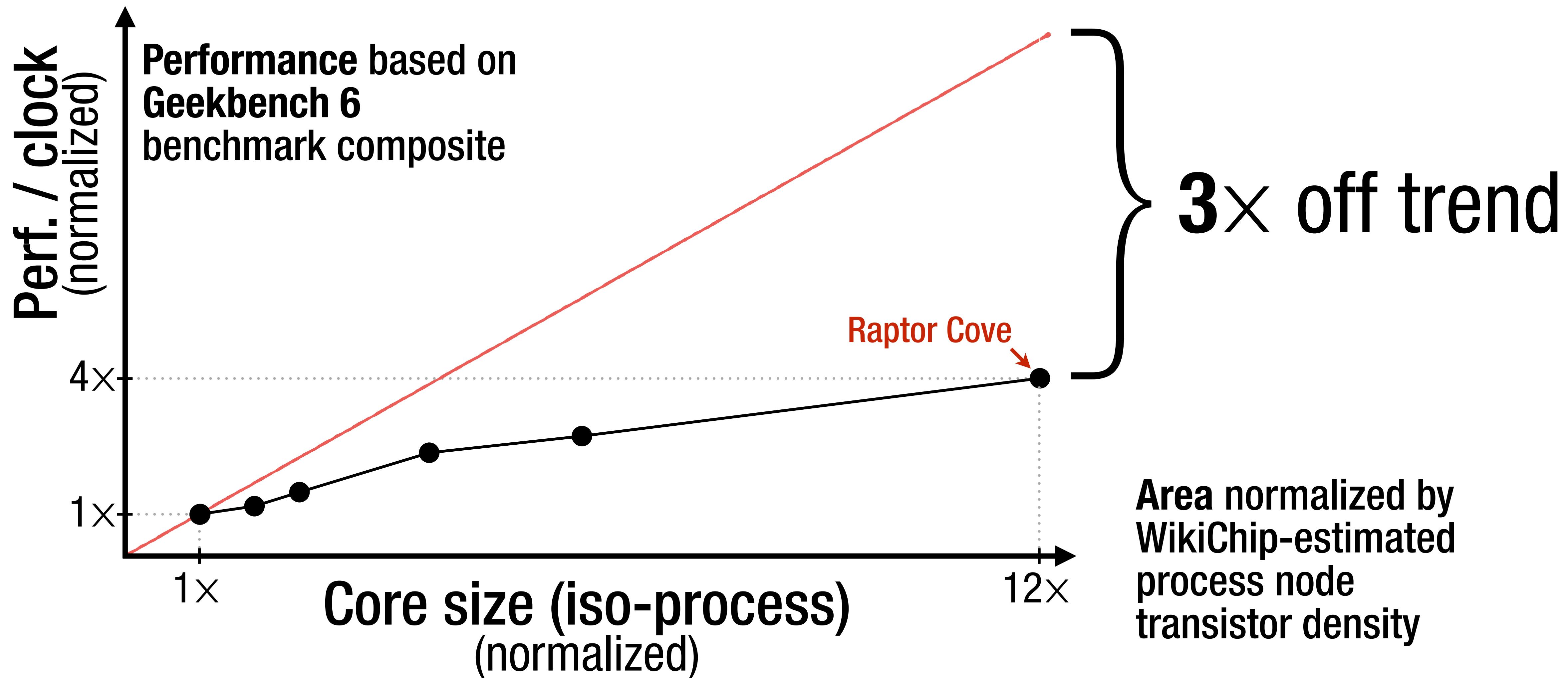
What to do with twice the silicon?



=
equal
area



Diminishing returns to scaling single-core performance



If we want to optimize **throughput**,
is there a **better way** to scale
performance?

Yes!

That's the focus of this class.

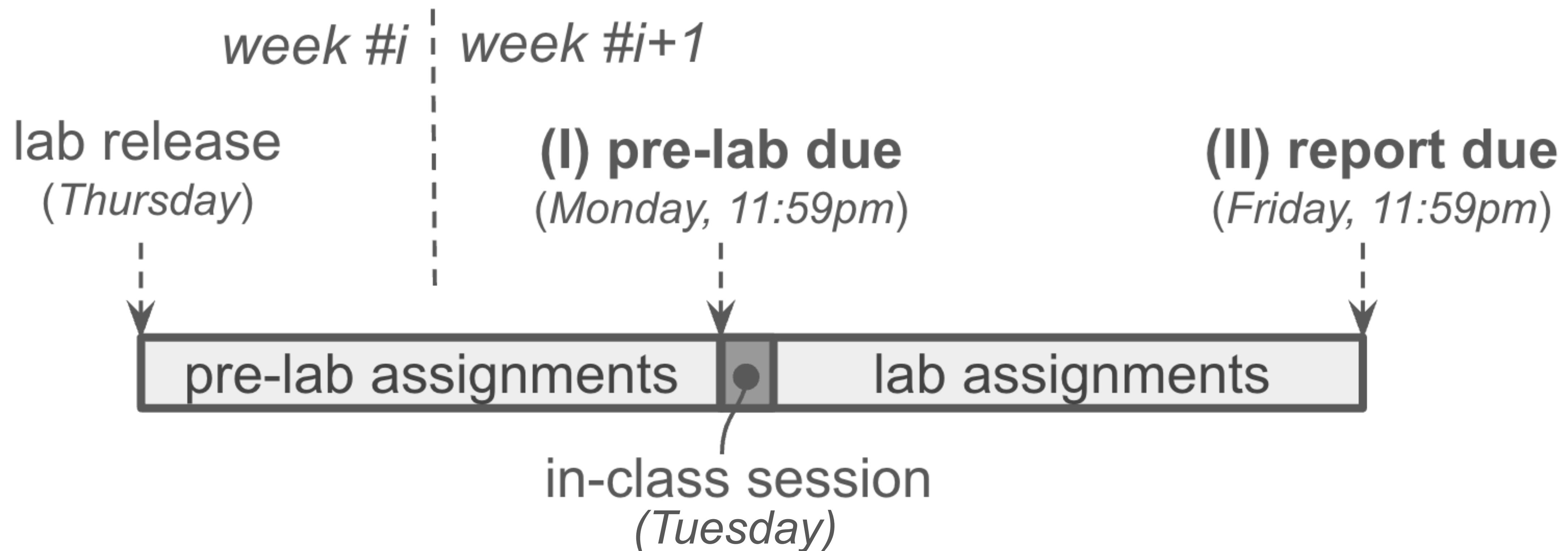
- 1 Better understand hardware
- 2 Practice programming it for **high performance**
- 3 Reasoning about performance from **first principles**

1 **Lecture**
Thu 2:30-3:30pm

2 **Programming
assignments**

3 **Lab session**
Tue 2:30-4:30pm

Weekly cadence:



First assignment out tonight,
first checkpoint due Monday (for Tuesday's lab)

Enrollment: 90 slots

Complete the survey today!

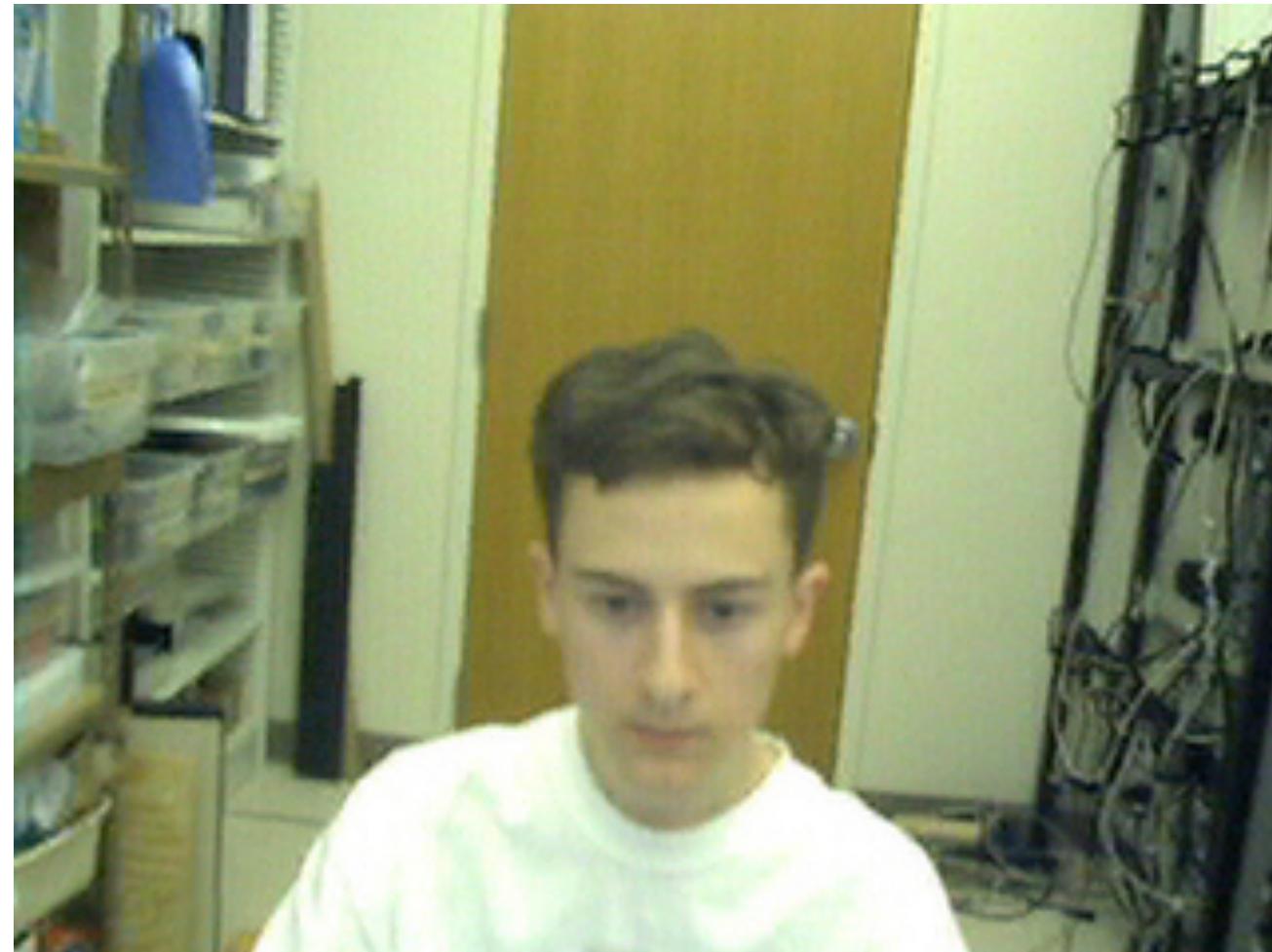
<https://bit.ly/6s894-enrollment-2025>

Expectations



Course web site:
accelerated-computing.academy

Your course staff



JRK

(Programming my first GPU,
Stanford Graphics Lab,
2001)



Manya



Sobhan



Rishab

Questions?